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SENSOR FUSION FOR A NETWORK OF PROCESSES/SYSTEMS WITH HIGHLY AUTONOMOUS SENSORS

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ABSTRACT

Data fusion and sensor management systems have largely been implemented with centralized and hierarchical architectures. Numerical and statistical methods are the most common data fusion methods found in these systems. Some recent research has emphasized distributed and decentralized systems, be it using analytical/quantitative techniques or qualitative reasoning methods. It appears that little has been done to define generic paradigms and theories to apply qualitative reasoning as an inference mechanism in distributed and decentralized systems. Based on other work by the authors, a sensor may be treated as a highly autonomous (decentralized) unit. In this context, this paper describes a distributed sensor-data-fusion paradigm and theory based on a previously developed theory to model sensors as highly autonomous units. Generic procedures are defined to reason and make decisions at the qualitative level. Therefore, fusion is done at a high-qualitative level, thus making it possible the implementation of intuitive (effective) methods to monitor, diagnose, and compensate processes/systems and their sensors. This paradigm facilitates distribution of intelligence (code and hardware) to the sensor level and peer-to-peer communication among sensors, controllers, and other devices in the system.

INTRODUCTION

Sensor fusion can be seen in two levels. One where only one physical sensor participates, and fusion entails interpretation of the current data point using a window of previously read points. That is, measurements from one sensor over a period of time (The measurement history of a sensor) are used to improve the quality and integrity of the current data point. A second level of sensor fusion implies participation of a group of physical sensors measuring the same or different parameters of a process. In this case, fusion entails the combination of the current data point of all sensors to improve the quality and integrity of one or many sensors of interest in the group. To further improve the measurement, both of these levels may be used simultaneously. For example, nuclear power plants have three of the same sensors in one location (three redundant sensors of the same kind at the same location and for the same measurement purpose). Three steps are taken to insure data integrity and accuracy. First data points from each sensor are averaged over a number of measurements. Second, a voting procedure eliminates the one average that is less similar. Third, the two remaining averages are averaged again to obtain the best interpretation of the measurement.

There are many analytical and statistical methods to perform sensor fusion. These use estimating tools such as equations describing physical phenomena monitored by the sensors, curve fitting methods, Kalman filtering, averaging, etc. These methods have been further augmented with expert-system type qualitative tools to reason using prepositional logic about the operation of the sensors and the measurand. More recent techniques that combine both logic and analytical methods such as Fuzzy Logic (Huntsberger, Jayaramamurthy, 1987) and Qualitative Process Theory (QPT) (Forbus, 1982, 1986) provide a more generic (formalized theory) approach to use of logic reasoning in sensor fusion.

Yet another issue in sensor fusion refers to the architecture used to implement a particular scheme. Sensor fusion architectures may be centralized-hierarchical or distributed-hierarchical. Architectures have tended to be centralized, since data from each sensor unit is usually transferred to a central place to be processed there along with data from other sensors. A distributed hierarchy means that each sensor unit processes its own data and sends a rich (integrated) set of information to any entity that may need to use it, including other sensors. In fact, each sensor in a distributed system has access to models of the processes in which the particular sensor is involved, along with information from all other sensors associated with the same processes. This approach defines each sensor as an autonomous agent in the context of particular processes. Moreover, it defines effectively a distributed-highly-decentralized system.

This paper presents a sensor fusion method that is distributed-highly-decentralized (DHD). It defines a sensor-process-controller physical network where each sensor is a highly autonomous sensor (HAS). Further, each HAS in the network can extract qualitative behaviors associated with the measurand and itself and thus fusion is done at a high qualitative level using logic reasoning about sensor and measurand behaviors. Moreover, the HAS model is generic and allows easy instantiation of any type of physical sensor as HAS. This is an important difference with respect to other models that use expert systems, in which extensive knowledge bases for each sensor-measurand pair must be created.

BACKGROUND

We are interested in using sensor fusion to interpret signals more accurately, to monitor behaviors of the sensors and measurands, to diagnose existing malfunctions or abnormal behaviors, and to predict future behaviors. As mentioned in the introduction, all of the existing sensor fusion methods known to the authors tend to interpret and monitor a system or process either totally using numerical and statistical tools or only logic reasoning. Exceptions to this statement include Qualitative Process Theory developed by Kuipers and implemented as QSIM (for qualitative simulation) (Kuipers, 1986) and other methods based on what is denominated *qualitative physics* in the artificial intelligence community (de Kleer, Williams, 1986). However, these theories have been developed as generic tools to reason qualitatively about physical phenomena. We are using some ideas and concepts from these researchers and are applying them to develop a DHD fusion scheme for a network of sensors and associated processes or systems.

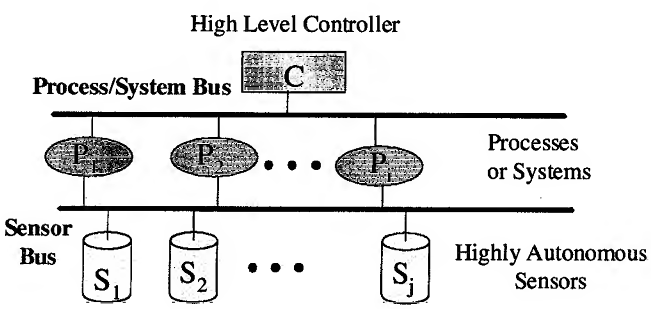
Kuipers' QPT was developed to describe qualitatively relationships among parameters of a process or system, which are normally described by analytical differential equations. Subsequently these qualitative descriptions may be used to reason and predict future behavior of the process/system. Later, Kuipers also developed MIMIC (Dvorak, 1989,1992)(Dvorak, Kuipers, 1996), in which he applied QPT specifically to the task of monitoring a process or system with multiple sensors. de Kleer's ATMS (Asumption Based Truth Maintenance System) (de Kleer, Williams, 1986), GDE (General Diagnostic Engine, Forbus' ATMI (1982) and SIMGEN(1987), DeCoste's DATMI (Dynamic Across Time Measurement and Interpretation) (1991), Durrant-Whyte's distributed decision making team(1990a, 1990b), Rodney Brooks' Subsumption Architecture, are all seemingly diverse approaches aimed explicitly at addressing the fundamental problem of how to combine, in the best possible manner, diverse and uncertain

sensor measurements and other information available in a multi-sensor system. The ultimate goal is to enable the system to estimate or make inferences concerning the state of the sensor's physical nature.

We present a fusion method that is inspired by QPT in its generality as a theory to reason about physical phenomena, but use typical system qualitative behaviors (responses to various inputs) instead of the qualitative equivalents of differential equations. The inspiration for this approach is DeCoste's DATMI (1991)(Dynamic Across Time Measurement and Interpretation). It requires the use of sensor models that are able to extract qualitative behaviors of themselves and of the measurands from the raw data. These sensor models have been previously developed by the first author and other researchers and are denominated Highly Autonomous Sensors (HAS) (Figueroa, Mahajan, 1994a, 1994b, 1995, Figueroa, Yuan, 2000). In this context, this paper describes a distributed hierarchical sensor-data-fusion theory that employs qualitative methods to interpret measurements, to reason, and to make decisions based on the measurement interpretations. In this manner, fusion is done at a high-qualitative level, thus making it possible the implementation of intuitive (effective) methods to monitor, diagnose, and compensate processes/systems and their sensors.

GENERAL FUNCTIONAL ARCHITECTURE

The proposed architecture is shown in Fig. 1. It is hard to imagine a system without top management level even though the lowest HAS level should operate in a highly autonomous manner. This contrasts with Durrant-Whyte's distributed sensor fusion (1988), which has no higher-level organization, and each sensor node also has to generate a control strategy. The task of the fully distributed sensor network as described in (Durrant-Whyte, 1988, Mutambara, 1998) is to control the system. The task for our system is to provide useful information for the operator or manager who is responsible for reacting promptly and correctly when abnormal behaviors occur, and to execute corrective action on the sensor operation when a fault has been evaluated and described with appropriate reliability and accuracy.



Many engineering systems consist of distributed devices, and decentralized architectures present us with a way to build global systems of the devices. In a fully decentralized system, all information is processed locally. Our decentralized sensor data-fusion system consists of a network of sensor nodes (highly autonomous sensors), each with its own processing capabilities. Sensors transfer each other and to a higher-level system only needed information that is not available within their particular domain. The bus-based architecture shown is typical of modern networked systems. Each sensor may be associated with one or more processes. And each process may be associated with other processes through input/output parameters. Processes need not be physically separate, but interaction among them should occur through input/output parameters.

As shown in Fig.1, at the lowest level, we have a distributed network of HAS's which have knowledge of the process model in which they partake. Each HAS detects normal and abnormal behaviors of itself and its measurand/environment using information in its own domain. It also provides necessary information for sensor fusion to both the lower HAS-level and the middle

Table I Measurand Behaviors and related concepts

SITUATION	DESCRIPTION	ASSOCIATED CONCEPTS
Constant input	Except for noise, the output remains at a constant level during the monitoring time.	Noise, monitoring time, constant level.
Monotonic change	Except for noise, the output increases or decreases linearly with time during the monitoring time	Noise, linear increase or decrease, monitoring time
Step input	Except for noise, the output remains constant during the monitoring time, then it suddenly jumps to a higher or lower level, where it remains during the monitoring time.	Sudden jump, noise, constant, monitoring time.
Harmonic	Except for noise, during the monitoring time, the output changes at a certain principal frequency. Other secondary frequencies may also be present.	Frequency, principal frequency, secondary frequencies, noise.

process-level. The lower HAS-Level sensor fusion aims at verifying whether the sensor works well independent of other sensors and provides reasonable behavior interpretations for the sensor and measurand. This is a function of the HAS model alone. The HAS-Bus-Level sensor fusion aims at combining higher level qualitative information from all HASs in the Sensor Bus associated with the same process. This further improves the interpretations of behaviors of each sensor and measurand. A final Process-Bus-Level fusion combines qualitative information linking associated processes. Again, this information further improves interpretation of behaviors of the sensors and measurands. It is noted that improving interpretations implies learning at the sensor and process levels and updating knowledge bases. The overall network should evolve, as time passes, into a fine tuned system with increasingly larger and more accurate knowledge bases. The top level monitors all processes. It uses information describing each process at the qualitative level to improve the entire network of processes. It may, for example, rearrange the schedule for the different processes.

EFFECTIVE FUSION FOR MONITORING, DIAGNOSIS, AND COMPENSATION

The Highly Autonomous Sensor (HAS)

Underlying the generalized distributed and decentralized architecture for multi-sensor fusion is the need to understand the nature of the information provided by each sensor. This requires a good sensor model detailing each sensor's underlying physical nature and the phenomenological nature of its measurements or the qualitative information these measurements provide. A highly autonomous sensor (HAS) model developed previously (Figueroa, Yuan, 2000) is a model that satisfies these requirements. A formal theory to model a HAS as developed by Figueroa and Mahajan (1994a, 1994b, 1995) and expanded by Figueroa and Yuan (2000). This theory is implemented in the HAS development environment, and is the essence of an engine for qualitative interpretation, reasoning, and decision-making (QIRD) by the sensor. The theory permits extraction of qualitative behaviors associated with the sensor, measurand, and disturbances. These behaviors, along with expected behaviors denominated "envisionments" and other qualitative knowledge that reside in the knowledge bases of the sensor and measurand, are used to perform QIRD and evaluate the integrity of the sensor and measurand. The envisionments are either entered by the user, or learned by the HAS.

The most important function of the HAS is the extraction of behaviors. They are defined by a succession of "concepts" which are, in turn, defined by properties that maintain constant values for a number of samples of the signal being read by the sensor. Table I shows how one

may determine the concepts that are needed to specify a behavior. For example, given the behavior "step change," a description is generated using concepts that are qualitatively assessed by the user. These concepts include constant, noise, sudden jump, and monitoring time. Each of these concepts has to be defined in terms of a set of properties and their values at every sample time. Sudden jump may be further defined as a combination of two concepts: ramp and fast exponential change

Sensor Fusion

Processes, in which the network of sensors is involved, must have some mathematical model from which qualitative descriptions may be extracted. These descriptions entail qualitative relationships among sensors' readings, which will be used for sensor fusion at the qualitative level. A very coarse qualitative description of the process may be sufficient for fusion of information from various sensors. For example, if one sensor detects a "step change," then all sensors should experience a "step change" of appropriate intensity. In general, any change in measurand behavior should be seen simultaneously by all sensors associated with the same process and other related processes, whereas sensor behaviors appear only at individual sensors.

A theory is being developed to formalize how qualitative relationships among sensor readings are represented. This theory is, in first instance, based on sensor and measurand behaviors detected by individual HAS's. It is also inspired by the theory of qualitative simulation developed by Kuipers (1986). In order to implement fusion, HAS models must be expanded to include information related to other sensors that monitor the same process. For instance, for each process a HAS (HAS1) monitors, it must have a module. In each module, there must be a set of qualitative relationships among the behaviors of HAS1 and all other HAS's of the process. The first relationship in all modules must indicate that any change in measurand behavior occurs simultaneously in all sensors associated with a process. Other relationships may refer to trends, such as if the signal from one HAS is changing linearly, another should changing appropriately (not necessarily linearly). Noise levels in the various HAS's should also be related. Thus, multiple qualitative relationships may be used to continuously monitor the operation of the system and sensors. In this manner, a unusual behavior associated with any HAS can be easily detected. In turn, detecting misbehaviors will simplify and speed diagnosis of malfunctioning elements.

Note that fusion is meant to occur at each HAS. Therefore, information need not flow through a process, but directly from one HAS to another. This distribution of intelligent processing turns each HAS into highly self-sufficient intelligent agents within the context of a set a processes and a network of HAS's.

The higher level unit (HLU) receives high level qualitative information from the processes. In turn, it sends high level requests and commands aimed at diagnosing a suspected problem or at improving the performance of all processes as a unit. For example, given a production line for a chemical product, the HLU may receive a message indicating that the product is not "fully cured" as it comes out of the last process. The unit may then program longer curing time in the oven heating process. In another example, a process may indicate to the HLU that a sensor is suspect of drifting behavior due to wear at a high duty-cycle. The HLU may then sound an alarm to have the sensor adjusted.

RESULTS AND DISCUSSION

An environment to model any sensors as a HAS is fully implemented. The environment has been tested with simulated and real data. It has been demonstrated that an individual HAS model is able to learn behaviors (measurand and sensor behaviors), store them in its database, and detect the learned behaviors when they occur again. Sensor fusion components of the HAS model are currently being implemented. A Theory and methodology have been developed, which take advantage of the qualitative behaviors extracted by HAS's distributed in a network of sensors.

Qualitative reasoning is the key inference mechanism in the data fusion architecture proposed in this paper. It has advantages over numeric and statistic methods for sensor data fusion in that: (1) it uses a qualitative level of description that permits representation of imprecise knowledge, (2) it permits reasoning about inexact systems in that it captures uncertainty by expressing multiple behaviors, and (3) it reduces an infinite number of infinitesimally close numeric behaviors to a small number of qualitatively distinct behaviors.

The HAS modeling environment is generic and supports expansion. In fact, it supports evolution through learning of behaviors. Aside from the logic rules used to reason with concepts and behaviors, other methods could be included such as Fuzzy Logic, Belief Theory, statistical methods, neural nets, and evolutionary techniques. One of the main contributions of this work is, in fact, that the modeling method is generic and open. Its strength is that it focuses on system qualitative behaviors in order to interpret the operation of a sensor and process. And furthermore, it exploits these behaviors to perform fusion at highly qualitative levels. In fact, human operators monitor and reason about sensors and systems based on qualitative behaviors extracted from the signals. This is a very fast and effective method to monitor and diagnose systems.

From the point of view of computing, the HAS modeling method and the overall structure for a network of sensors and processes, conforms to a highly distributed system where the information that is transferred among its components is of high level. This greatly reduces the bus traffic.

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